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A Motif-based Mission Planning Method for UAV Swarms Considering Dynamic Reconfiguration

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ABSTRACT

Influenced by complex terrain conditions of combat environments and constrained by the level of communication technology, communication among unmanned aerial vehicles (UAV) is greatly restricted. In light of this situation, mission planning for UAV swarms under limited communication has become a difficult problem. This paper introduces motifs as the basic unit of configuration and proposes a motif-based mission planning method considering dynamic reconfiguration. This method uses multidimensional dynamic list scheduling algorithm to generate a mission planning scheme based on the motif-based swarm configuration solution. Then it incorporates order preserved operators with NSGA-III algorithm to find Pareto front solutions of all possible mission planning schemes. The feasibility of this mission planning method is validated through a case study.

Keywords: Mission planning; UAV swarms; Dynamic reconfiguration; MDLS; NSGA-III algorithm

NOMENCLATURE

UAV	Unmanned aerial vehicle
DUAV	UAV for decision-making
RUAV	UAV for reconnaissance
AUAV	UAV for attack
RAUAV	UAV for reconnaissance and attack
CUAV	Communication relay UAV
MDLS	Multidimensional dynamic list scheduling
MCT	Mission completion time
ANOCC	Average number of changed connections
ANOUU	Average number of UAVs used each time
MOEA	Multi-objective evolutionary algorithm

1. INTRODUCTION

As unmanned aerial vehicles (UAV) swarms play a more and more important role in the field of combat, mission planning for UAV swarms has become a research hotspot[1]. Current research discusses the problem with two aspects:

(i) Researcher applied intelligent optimisation algorithm to solve mission planning problems. Atencia[2] presented a multi-objective genetic algorithm for solving complex mission planning problems involving a team of UAVs and a set of GCSs. Lamont[3] developed a parallel mission planning system based on multi-objective evolutionary algorithm.

(ii) Due to the complexity the problem, some research studied the problem in simulation systems. James[4] designed and implemented a comprehensive mission planning system which integrated several problem domains for UAV swarms in the simulation system[4]. Wei[5], *et al.* proposed an operation-time simulation framework for UAV swarm configuration and mission planning.

These research studied mission planning problems for UAV swarms and achieved fruitful results. However, these mission planning methods did not take restrictions of communication among UAVs into consideration. Due to restrictions on the communication technology of the UAV such as bandwidth, frequency and so on, communication among UAVs is greatly limited[6]. Moreover, UAVs usually face complex geographical environment and strong electromagnetic interference of the enemy during combat process, which both affect the communication between UAVs to a great extent. As a result, mission planning for UAV swarms under limited communication has become a difficult problem.

In light of this situation, this paper introduces motif as the basic unit of configuration which only requires a few communication connections among UAVs. Based on the motif configuration, the paper proposes a motif-based mission planning method considering dynamic reconfiguration under limited communication. The paper put forwards two operators to keep the logical corrections between tasks. Through applying NSGA-III algorithm, we realise finding out the optimal schemes that meet the requirements from a large number of feasible schemes. As shown in Fig. 1, we employed a three-step process to construct an optimised mission planning scheme for a given mission structure. Firstly, the mission is decomposed into tasks having intrinsic logical relation. Secondly, tasks are assigned to motifs. We use multidimensional dynamic list scheduling (MDLS) algorithm to generate schemes. Lastly, we applied NSGA-III algorithm to choose a suitable task execution sequence to achieve better operational effectiveness. This paper mainly focuses on the two latter steps.

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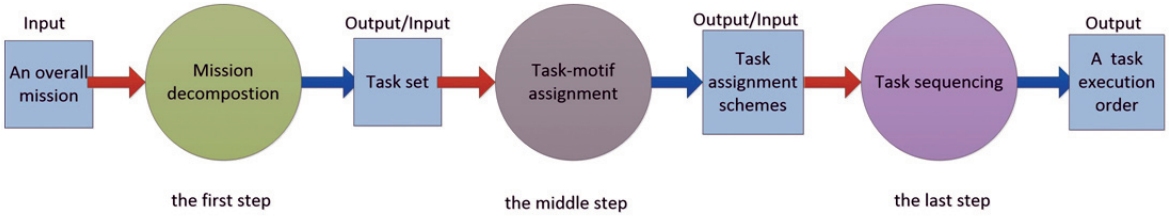

Figure 1. Motif-based mission planning framework diagram.

2. MOTIF-BASED MISSION PLANNING MODEL

2.1. Mission Decomposition

Mission decomposition is the foundation step to build a mission planning model. Firstly, we used a goal decomposition method to decompose the mission into a task set $T_i(i=1,2,...,N_T)$.

Secondly, a task graph[7] was used to detail the following correlations between tasks:

(i) Task priority[8]: in the case of insufficient resources, the task located at the front of the priority chain has a priority to be carried out earlier. In the case of sufficient resources, tasks can be concurrent simultaneously.

(ii) Task precedence[9]: in a task precedence chain, the order of task T_i in front of task T_j means task T_i should be completed before task T_j start.

As shown in Fig. 2, we used a directed task graph to indicate priority relationships between tasks. We regarded task precedence correlations as special priority relations that have strict restrictions in time.

Thirdly, it is a complicated process to check whether a priority order is feasible, we decompose the task graph into several task priority order chains, as shown in Fig. 3.

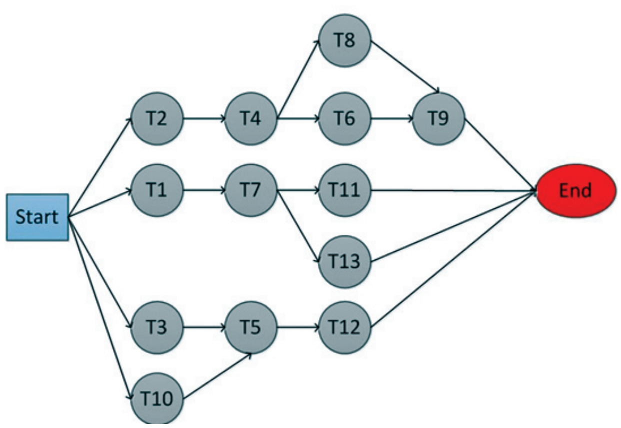

Figure 2. Task priority graph.

2.2 Task Assigning to Motif

2.2.1 *Motif-Based Configuration*

Network motif is the characteristic pattern of interaction in complex networks. Compared with random network, motif comes up more frequently in complex networks. Motif is of great significance as they can reflect the function to be effectively realised in a framework[10]. Lee & Lee[11] proposed a motif-based measurement method of combat effectiveness. We used motifs as basic units of configuration for UAV swarms in the mission planning model.

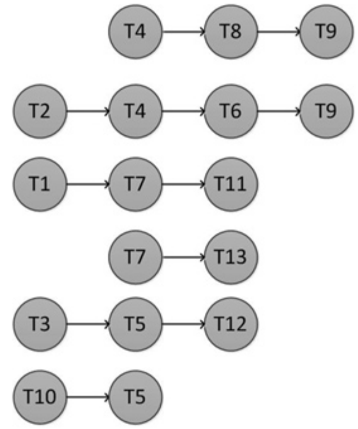

Figure 3. Task priority order chains graph.

UAVs are usually divided into five classes: DUAV, RUAV, AUAV, RAUAV, and CUAV according to their functions. Through observing and studying the UAV operational network, we abstracted six types of motif which frequently appear and have a realistic significance out of the network in Fig. 4. Considering the lack of decision-making ability, all operations need the participation of the DUAVs.

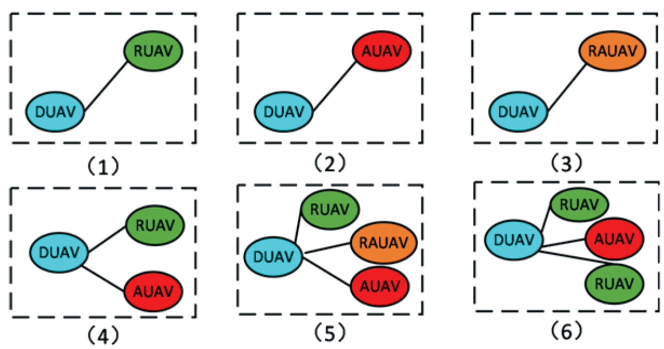

Figure 4. Basic motif-based configuration diagram.

2.2.2 *Task Assignment*

In UAV swarm operations, communication has an important effect on combat process and combat results. Based on the traditional method of the capacity requirement vector, we add the information demand vector as a constraint from tasks mapping to motifs. As is seen in Fig. 5, task requirement is refined into capacity demand and information demand. We can get the kinds and numbers of motifs that are required for completion of a task through calculation of capacity demand and information demand.

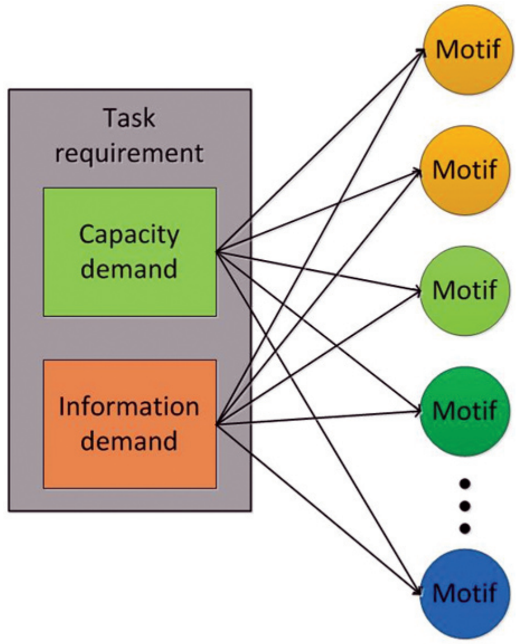

Figure 5. Task requirement mapping diagram.

2.2.2.1 Capacity demand

Combing the characteristics of UAV swarm operation with the traditional capacity demand vector, we propose a new capacity demand vector which has six components: low altitude detection capacity, aerial reconnaissance capacity, sky-to-ground attack capacity, sky-to-sky attack capacity, patrol strike capacity and information processing capacity. Capacity demands are considered met when the capacity vector of UAV swarm is component wise more than or equal to capacity demand vector C_h.

The six capacities of the motif are defined based on the kind and number of UAVs, the capacities of each UAV and the connection the motif involves. The j^{th} capacity of motif i is β_{ij}.

$$\beta=\begin{bmatrix}\beta_{11} & \cdots & \beta_{16}\\ . & \cdots & .\\ \beta_{61} & \cdots & \beta_{66}\end{bmatrix} \tag{1}$$

n_k (the number of motif k) must satisfy the following linear inequality:

$$\begin{pmatrix}n_1 & n_2 & n_3 & n_4 & n_5 & n_6\end{pmatrix}\cdot\beta^T \geq C_h \tag{2}$$

2.2.2.2 Information demand

Information demands are usually reflected by two indicators: the average degree of network and the clustering coefficient. The average degree of network ω is measured:

$$\omega=\frac{l}{n} \tag{3}$$

$$l = n_1 + n_2 + n_3 + 2n_4 + 3n_5 + 3n_6 \tag{4}$$

$$n = 2n_1 + 2n_2 + 2n_3 + 3n_4 + 4n_5 + 4n_6 \tag{5}$$

The average degree represents the average number of UAVs per UAV connected[12].

The clustering coefficient τ is measured by:

$$\tau=\frac{2l}{n(n-1)} \tag{6}$$

Representing the probability of communication between the two UAVs[13].

To complete the task, ω and τ need to be equal or more than the required information interaction ω_t and the required equipment connectivity τ_t for the task completion.

Through task assignment to motifs, we can calculate the kind and number of motifs that are required for a task completion. In our model, we characterise every task T_i by the following basic attributes:

(i) Estimated completion time $t_i (i = 1, 2, \ldots N_T)$;
(ii) Motif demand vector $[m_{i1}, m_{i2}, \ldots, m_{i6}]$, where m_{ij} is the number of motif j required for successful completion of task T_i.

2.2.3 Motif Operation Network

CUAVs have a strong communication capacity with wide bandwidth and long communication distance. Combining CUAVs with motifs, we propose a new UAV operation network which has an enhanced communication ability and an expanded the communication range. Detailed connection way is seen in Fig. 6.

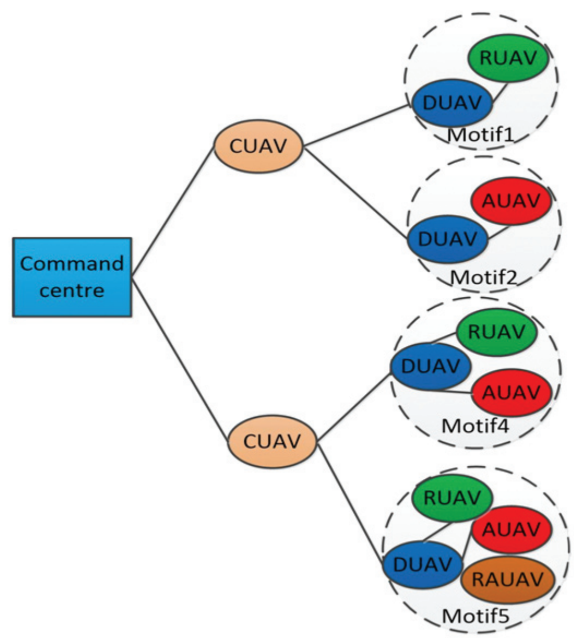

Figure 6. Motif operation network diagram.

2.3 Mission Planning

After mission decomposition and task assignment, we get the kinds and numbers of motifs that are required for those tasks. In this section, we study how to dispatch existing UAVs to constitute motifs and construct a mission planning scheme to achieve better combat effectiveness.

2.3.1 MDLS for UAV Scheduling

The UAVs scheduling problem is the key issue in UAV swarm mission planning. MDLS is often used in combat scheduling and has achieved good results[14,15]. We used it in this study to dispatch the UAVs. The MDLS contains two main steps:

Step 1: Select the task to be processed.

Step 2: Select UAVs to be assigned to motifs required for task completion.

In Step 1, a ready task is selected (a task becomes ready when all tasks that have a priority over it have started and all its predecessors have been completed).

In Step 2, spare UAVs are selected (UAVs are spare when they are not in working condition). If spare UAVs can constitute motifs that task completion require at that moment, the task can start. If not, the task needs to wait until processing tasks have been completed and the UAVs they occupied will become spare. The task will not start until spare UAVs meet the demands of task completion.

2.3.2 *Dynamic Configuration*

In the MDLS algorithm, all tasks start at the moment a group of tasks are completed. All CUAVs disconnect motifs when tasks are completed and connected to motifs when tasks start every time. As a result, the number of altered connections attached to the CUAVs is constant, marked as n_c. To reduce the number of altered connections between the UAVs, motifs required for tasks to begin maintain as many as possible for tasks that were already completed. If customary motifs cannot meet the demands of upcoming tasks, we used remaining motifs after selection and spare UAVs (UAVs not involved in any motif) to reconstruct needed motifs. As is seen in Fig. 7, the remaining motifs after selection disconnected all connections for the reconstruction of new motifs.

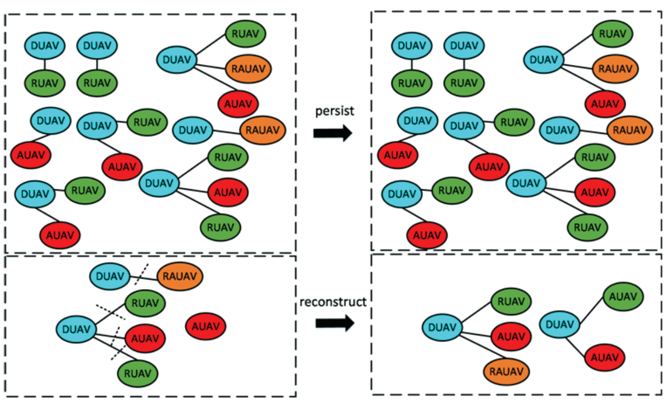

Figure 7. Preservation and reconstruction of motifs graph.

2.3.3 *Effectiveness Index*

In this paper, according to the characteristics of unmanned combat, we mainly studied three operational effectiveness indexes.

(i) MCT

(ii) ANOCC: The topology changes of an UAV network lead to communication delays[16]. A decrease in ANOCC will help reduce communication delays.

(iii) ANOUU: The smaller ANOUU is, the larger the number of spare UAVs is, ensuring task completion.

2.4 Mathematical Model of Mission Planning Optimisation

2.4.1 *Optimisation Variables*

In the mathematical model of mission planning, we use the execution order of tasks as the variables in mission planning optimisation and the execution order is subjected to restrictions of the task graph.

2.4.2 *Objective Functions*

(i) MCT t: $t = \max(FT)$

(ii) ANOCC: There are two cases when we calculated altered connections in motifs. In the first case, when a set of tasks are completed, no task would start as spare UAVs could not meet the demands. All connections in the motifs required for these completed tasks are lost to avoid the enemy's investigation. The number of altered connections is marked

$$n_d(t_j) = m(t_j)\bullet(1,1,1,2,3,3)^T \tag{7}$$

$m(t_j)$ is the total motif vector of completed tasks; and t_j is the completion time of these tasks. In the other case, one or more tasks begin at the moment when some tasks are completed. The number of altered connections is marked

$$n_r(t_k) = \left|m_c(t_k) - m_s(t_k)\right|\bullet(1,1,1,2,3,3)^T \tag{8}$$

$m_c(t_k)$ is the total motif vector of tasks that are completed at t_k. $m_s(t_k)$ is the total motif vector of tasks that start at t_k. The number of total altered connections is n

$$n = \sum_{t_j \in t_c \setminus t_s} n_d(t_j) + \sum_{t_j \in t_c \cap t_s} n_r(t_k) + n_c \tag{9}$$

(iii) ANOUU: The number of used UAVs changes once the UAV connection network changes. $T = t_s \cup t_e$ is the set of times at which UAV connections change (arrange the time in the set T according to the order from small to large). The number of used UAVs from $T(i)$ to $T(i+1)$ is

$$s(i) = \sum_{\substack{t_s(k) \le T(i) \\ t_e(k) \ge T(i+1)}} m_k \bullet (2,2,2,3,4,4)^T \tag{10}$$

ANOUU is

$$s = \frac{1}{n(T)} \sum_{i=1}^{n(T)} s(i) \tag{11}$$

3. PLANNING SCHEME OPTIMISATION USING A CUSTOMISED NSGA-III ALGORITHM

We applied a customised NSGA-III algorithm which has been demonstrated to outperform most MOEA approaches on many-objective benchmark problems[17]. To keep candidates conforming to all task priority chains, we incorporated order preserved operators with NSGA-III algorithm.

3.1 Crossover-Op Operator

By using the crossover-op operator, the offspring chromosomes keep relative orders in parent chromosomes. First, all chromosomes of the population were paired. Then, chromosome pairs were selected from them with a probability of *pc*. The middle point divided parent chromosomes into two

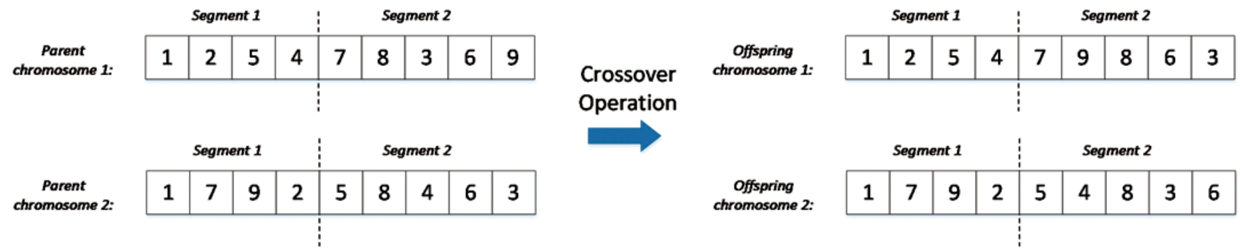

Figure 8. Example of the crossover operator.

Figure 9. Example of the mutation operator.

gene segments located at $\left\lceil \dfrac{N_T}{2} \right\rceil$. As is seen in Fig. 8, new offspring chromosomes were constructed as follows:

(a) Gene segment 1 remained unchanged;

(b) Gene segment 2 was constructed by following the sorting of these tasks in the other parent.

3.2 Mutation-Op Operator

First, chromosomes of *Pc* are selected from *P* with a probability of *pm*. Each chromosome of *Pc* mutates with a probability of *mu*. This mutation operator uses the exchange of a two points approach. Then, we need to select a point that can be exchanged, marked as *pi*.

The operator select out previous tasks of *pi* in priority chains and archive them in set *Bi*. Similarly, the next task set of *pi* is got, denoted as *Ai*. The exchangeable range of *pi* which contained the fewest points in the chromosome is denoted as [*bi,ai*](*bi* ∈ *Bi, ai* ∈ *Ai*), representing a gene segment from *bi* to *ai* without *bi* or *ai*.

Algorithm 3. Function mutation-op (*P, pc, mu*)

Input: Initial population members, P of size N, mutation percentage, pm, mutation occurring probability, mu, priority order chains, Tor

Output: Offspring Om

```
1   Pc←popselection(P, pm);
2   t=1;
3   while t ≤ N · pc
4       k← random(0,1);
5       if k > mu
6         Om(t)←chromosome(t);
7         k=k+1;
8       else pi←rand(random((0,N_T)));
9       if pi is not exchangeable
10          Go to line 7;
11          else C←exchangeableset(chromosome(t), Tor, pi);
12          q ← rand(random((0,|C|)));
13        Om(t)← exchange(chromosome(t),pi,C(q));
14      end
15    end
16  end
```

Figure 9 provides an example of the mutation operator. Task priority chains: T2-T1-T6-T7; T2-T4-T3; T8-T6-T5-T9; We randomly selected T4 and found the set {T1, T8, T6} of points which could be exchanged with T4. Next, we have chosen T8 for the exchange and obtain a new offspring chromosome.

4. CASE STUDY

A joint group of UAVs is assigned to complete a military mission that includes capturing a seaport and an airport. The mission geographic layout is shown in Fig. 10. The mission is completed by 6 CUAVs, 20 DUAVs, 18 RUAVs, 16 AUAVs, and 8 RAUAVs according to plan and deployment. Commanders want to make a scheme which completes the mission within 75 min, keeps ANOCC not more than 170 and ANOUU not more than 45 simultaneously. Due to the barrier of the hills and the electronic interference of the enemy, communication among UAVs is greatly restricted. We use the communication-restricted case to verify the motif-based mission planning method.

The mission is decomposed into 15 detailed tasks which have internal priority and precedence relationship orders through applying goal decomposition method, as shown in Fig. 11. More concretely, the task execution priority order need to satisfy the task priority chains: T4-T1-T2, T8-T7-T3, T9-T10-T14-T15, and the task precedence order chains: T10-T14, T7-T3.

Through linear inequalities of capacity demand and

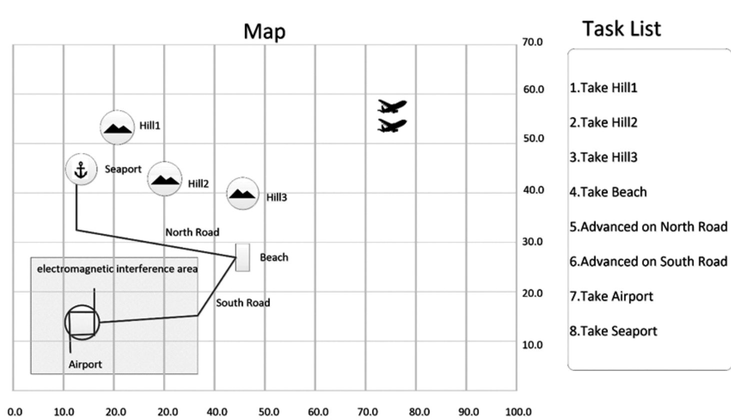

Figure 10. Geographical constrains and mission tasks for the case.

information demand, we work out the kinds and numbers of motifs that are required for each task's completion, shown in Table 1.

Table 1. Detailed information of tasks

Motif	M1	M2	M3	M4	M5	M6	Time (min)
T1	3	3	2	4	3	2	15
T2	2	4	3	3	4	3	8
T3	2	1	2	3	0	1	7
T4	1	2	1	0	1	1	12
T5	1	0	1	1	0	1	9
T6	0	1	1	0	1	0	5
T7	2	1	0	1	2	1	6
T8	1	2	1	0	1	2	11
T9	3	1	0	1	0	2	10
T10	2	0	1	2	1	0	18
T11	2	3	2	1	2	2	10
T12	2	1	0	0	1	1	8
T13	1	3	2	1	1	0	9
T14	0	2	2	1	0	3	11
T15	2	0	3	1	2	2	7

We encoded the solution and applied the customised NSGA-III algorithm to choose mission planning schemes for UAV swarms. We can get different mission planning schemes through changing task execution priority order. There are $C_{15}^{4} \cdot C_{11}^{3} \cdot C_{8}^{3} = 12612600$ feasible execution orders. Thus, 12612600 feasible mission planning schemes are provided for us to choose. Selecting schemes that meet the requirements on three dimensions is a hard work which consumes much time. The application of NSGA-III-op algorithm realises fast iteration and convergence, and greatly shortens the time of mission planning, achieving real-time planning. We can select schemes through optimisation of three operational effectiveness indexes respectively or simultaneous constraints on three dimensions. After 20-time Matlab simulation experiments, we merge all non-dominated points and plot them in Figs. 12 and 13, which are representations of the last generation. We can choose suitable mission planning schemes that meet the requirement through observing Figs. 11 and 12. There are 2 mission planning meet the requirements. Their task execution priority orders are: 1.T6-T4-T8-T13-T9-T10-T12-T7-T1-T14-T5-T2-T11-T15-T3, 2. T5-T9-T10-T4-T1-T14-T6-T15-T8-T13-T12-T7-T3-T11-T2. Thus, we get two suitable mission planning schemes after the execution priority orders are inputted.

Figure 12 is a 3D figure of the population members of the last generation, showing 3 objects, representing Pareto front solutions of all possible mission planning schemes. Figure 13 is a 2D figure of the population members where each represents 2 objectives of the 3. We observe that the mission completion time has a significant negative relationship with the average number of used UAVs every time from Figs. 12 and 13.

Observing the first graph in Fig. 13, we found there are two mission planning schemes whose completion time is less

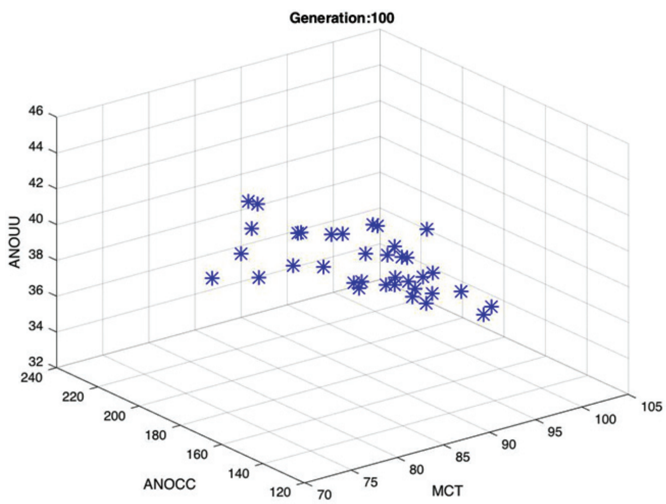

Figure 12. 3D Pareto front of last generation.

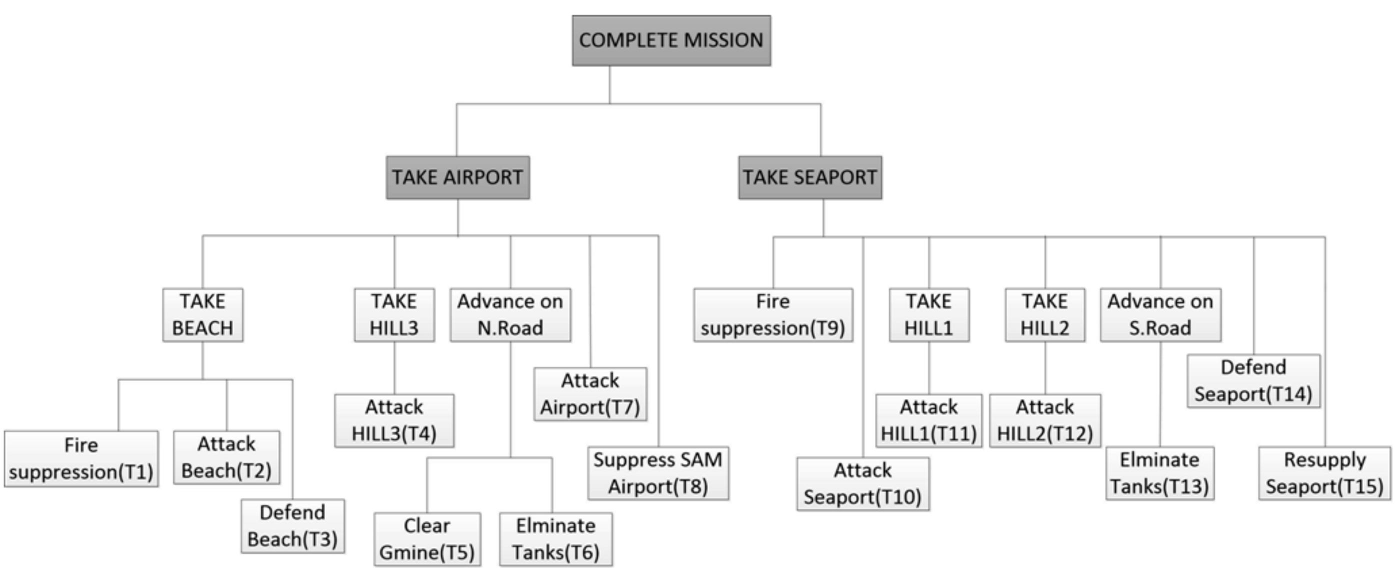

Figure 11. Mission goal decomposition for the case.

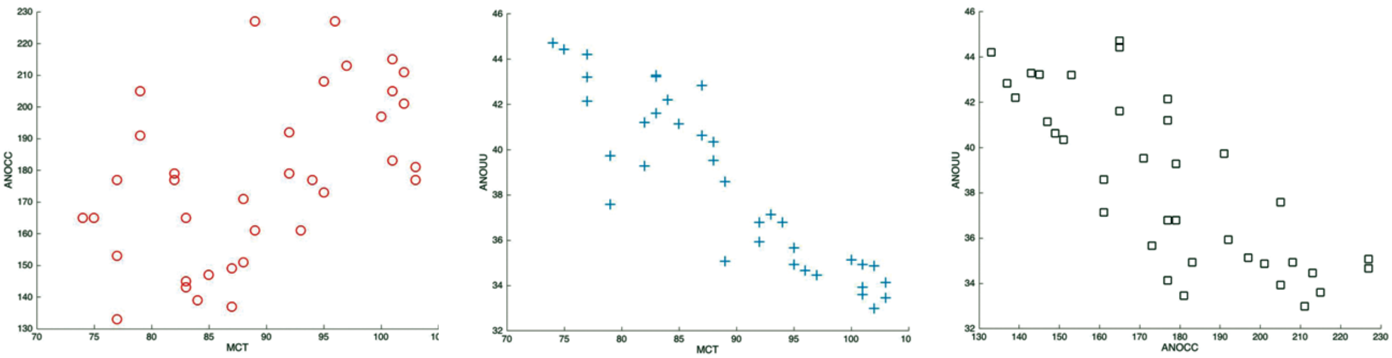

Figure 13. 2D Pareto front of last generation.

than 75 min. The ANOCC of these two schemes is all 165, less than 170. We found two schemes in the second graph in Fig. 13. Their ANOUU are 44.4 and 44.7. In the third graph, the schemes whose ANOCC are located at 165 are of 44.4 ANOUU and 44.7 ANOUU. Through observing Figs. 12 and 13, we find out the two mission planning schemes that meet the requirements easily.

The case study validate that we can find out the mission planning schemes suiting requirements on three dimensions through applying the motif-based mission planning method.

5. CONCLUSIONS AND FUTURE WORKS

This paper presented a motif-based mission planning method for UAV swarms under limited communication. We incorporated NSGA-III algorithm with the motif-based model to get a suitable task execution priority order. It automatically generated a good mission planning scheme as the execution order was inputted to MDLS algorithm. The feasibility of the mission planning method was validated through a case study.

In future works, we would like to incorporate the motif-based planning method with simulation methods to further verify the method.

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CONTRIBUTORS

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